To further increase the accuracy of the comparison, each yearly vintage is divided into four quarterly portfolios, i.e. first, second, third and fourth quarters. All of the 1993 portfolios of the same quarterly age are summed and divided by the total number of all the loans with the same respective age. Referring again to Fig. 3, the present invention separately compares the 1993 and 1994 24 month old loans, then the 21 month old loans and so on. The actual mathematical calculations/analysis comparing loans originated in 1993 and 1994 and the manner of calculating bad rates is shown below in Tables I, II and III.

TABLE I

	Age (Months)	3	6	9
1993 Vintage	# of Loans (n)	n_3	n_6	n_9
	BAD rate (r)	r_3	r_6	r_9
	STD	$Sqrt(r_3*(1-r_3)/n_3)$	$Sqrt(r_6*(1-r_6)/n_6)$	$Sqrt(r_9*(1-r_9)/n_9)$
1994 Vintage	# of Loans (N)	N_3	N_6	N_9
	BAD rate (R)	R_3	R_6	R_9
	STD	$Sqrt(R_3*(1-R_3)/N_3)$	$Sqrt(R_6*(1-R_6)/N_6)$	$Sqrt(R_9*(1-R_9)/N_9)$
1994-1993	Difference (R-r)	R_3-r_3	R_6-r_6	R_9-r_9
	STD of (R-r)	$STD_3=Sqrt(r_3*(1-r_3)/n_3+R_3*(1-R_3)/N_3)$	$STD_6=Sqrt(r_6*(1-r_6)/n_6+R_6*(1-R_6)/N_6)$	$STD_9=Sqrt(r_9*(1-r_9)/n_9+R_9*(1-R_9)/N_9)$
	Upper Bound	$+1*STD_3$	$+1*STD_6$	$+1*STD_9$
	Lower Bound	$-1*STD_3$	$-1*STD_6$	$-1*STD_9$

TABLE II

	Age (Months)	12	15	18
1993 Vintage	# of Loans (n)	n_{12}	n_{15}	n_{18}
	BAD rate (r)	r_{12}	r_{15}	r_{18}
	STD	$Sqrt(r_{12}*(1-r_{12})/n_{12})$	$Sqrt(r_{15}*(1-r_{15})/n_{15})$	$Sqrt(r_{18}*(1-r_{18})/n_{18})$
1994 Vintage	# of Loans (N)	N_{12}	N_{15}	N_{18}
	BAD rate (R)	R_{12}	R_{15}	R_{18}
	STD	$Sqrt(R_{12}*(1-R_{12})/N_{12})$	$Sqrt(R_{15}*(1-R_{15})/N_{15})$	$Sqrt(R_{18}*(1-R_{18})/N_{18})$
1994-1993	Difference (R-r)	$R_{12}-r_{12}$	$R_{15}-r_{15}$	$R_{18}-r_{18}$
	STD of (R-r)	$STD_{12}=Sqrt(r_{12}*(1-r_{12})/n_{12}+R_{12}*(1-R_{12})/N_{12})$	$STD_{15}=Sqrt(r_{15}*(1-r_{15})/n_{15}+R_{15}*(1-R_{15})/N_{15})$	$STD_{18}=Sqrt(r_{18}*(1-r_{18})/n_{18}+R_{18}*(1-R_{18})/N_{18})$
	Upper Bound	$+1*STD_{12}$	$+1*STD_{15}$	$+1*STD_{18}$
	Lower Bound	$-1*STD_{12}$	$-1*STD_{15}$	$-1*STD_{18}$

TABLE III

	Age (Months)	21	24	27
1993 Vintage	# of Loans (n)	n_{21}	n_{24}	n_{27}
	BAD rate (r)	r_{21}	r_{24}	r_{27}
	STD	$Sqrt(r_{21}*(1-r_{21})/n_{21})$	$Sqrt(r_{24}*(1-r_{24})/n_{24})$	$Sqrt(r_{27}*(1-r_{27})/n_{27})$
1994 Vintage	# of Loans (N)	N_{21}	N_{24}	N_{27}
	BAD rate (R)	R_{21}	R_{24}	R_{27}
	STD	$Sqrt(R_{21}*(1-R_{21})/N_{21})$	$Sqrt(R_{24}*(1-R_{24})/N_{24})$	$Sqrt(R_{27}*(1-R_{27})/N_{27})$
1994-1993	Difference (R-r)	$R_{21}-r_{21}$	$R_{24}-r_{24}$	$R_{27}-r_{27}$
	STD of (R-r)	$STD_{21}=Sqrt(r_{21}*(1-r_{21})/n_{21}+R_{21}*(1-R_{21})/N_{21})$	$STD_{24}=Sqrt(r_{24}*(1-r_{24})/n_{24}+R_{24}*(1-R_{24})/N_{24})$	$STD_{27}=Sqrt(r_{27}*(1-r_{27})/n_{27}+R_{27}*(1-R_{27})/N_{27})$
	Upper Bound	$+1*STD_{21}$	$+1*STD_{24}$	$+1*STD_{27}$
	Lower Bound	$-1*STD_{21}$	$-1*STD_{24}$	$-1*STD_{27}$

Table I contains the calculations and comparisons for 1993 and 1994 loans which have vintage ages of 3, 6 and 9 months; Table II does the same for loans aged 12, 15 and 18 months; and Table III does so for loans that are 21, 24 and 27 months. The first line in Tables I-III sets forth the total number (n_3, n_6, etc.) of loans of the given vintage. The second line in the

Tables sets forth the bad rates (r_3, r_6, etc.) for each vintage age. The third line calculates the standard deviation (STD) of the bad rate, using the indicated equations. The first three lines of Table I supply the relevant information and calculations for the 3, 6 and 9 month old 1993 vintage. The next three lines of Table I supply the same information for the 1994 vintage. The bottom four lines of Table I calculate the differences and compare the results for 1993 and 1994 vintage years. The last two lines calculate upper and lower bounds for the standard of deviation. The two bounds are plus one and minus one standard deviation, but management can set this based on their tolerance for default risk. These calculations constitute the Crus Classes method 30 of the invention whose effect can be appreciated from reviewing the analysis results plotted in Fig. 4.

That is the values calculated in Tables I, II and III above for the differences between vintages 1994 and 1993 are plotted in the graph of Fig. 4 relative to a zero percentage base 71. The curve 70 represents the magnitude of the difference in the "bad" rates of loans of the same age. The value of the curve 70 equals r_3-R_3; r_6-R_6; etc. shown in Tables I-III. One would be tempted to assume that the 1994 vintage performs better than the 1993 anytime the value of the curve 70 goes over zero

percent and vise versa. However, such a mode of analyzing the data would be subject to reaching wrong conclusions due to statistical variations. To overcome this drawback, it is more significant to ask whether a vintage that appears to perform better does so in fact or whether it merely reflects a temporary phenomenon. To answer the question, the invention uses a hypothesis testing technique which allows the analyst to set a confidence interval which is adjustable to allow for different corporate risk tolerance levels. Thus, the confidence interval can be equated to the amount of risk tolerance management will accept in originating, purchasing, retaining or servicing loan portfolios. These confidence intervals can also be used in product profitability and capital allocations. Management can then rank the vintages by product, program, age and size. To this end, the Tables presented above also calculate the standard deviation of the difference in performance and sets upper bounds and lower bound of +1 and -1 standard deviations for each quarterly vintage. These upper and lower limits which appear in the last two lines of Tables I, II, III are plotted in the form of curves 66 and 68 in Fig. 4. The area between the curves 66 and 68 is an area of uncertainty.

With this in mind, since the invention superimposes the curve 70 over the area of uncertainty, one can state with greater certainty which vintage performs better only in the areas outside the area of uncertainty. Thus, the graph of Fig. 4 shows that the 1994 loan vintages are "better" than corresponding 1993 loan vintages for loans that are 6, 21 and 24 months old. On the other hand, the 1993 vintage appears to be better for loans that are 27 and 30 months old. During other months, the result is too close to conclude with the chosen degree of certainty which vintage is better. The chart of Fig. 4 underscores the fallacy of the prior art in referring to yearly vintages as better or worse. One must be more specific as to time and other criteria, since relative performance changes dynamically with time.

While the invention has been described above in relation to the consideration of vintages in yearly quarterly units, note that in the loan industry exogenous factors such as changes in economy, unemployment and inflation are time varying factors that vary greatly over an annual interval and therefore the system of the invention permits analysis based on the choice of any interval unit. The important thing to realize is that in general, a new mortgage loan is more sensitive to small changes in delinquency performance than an older

mortgage. This is shown by widening of the confidence interval bands over time. So in essence, the application of the above described Crus Classes method corrects for this fact.

The invention also takes and adjusts the vintage rating based on quality comparisons for different volatilities of default. In essence, using the system lets the user to set policies with respect to volatilities of default which is another form of risk management. This is new to the industry.

The confidence level in the assessment of the difference in quality between groups of loans depends to a certain degree on the sample size of the loans. For small groups of loans, one will always be less certain of their performance. The real question is how much less certain. This is answered with the Crus Classes method. The Crus Classes method also automatically adjusts the comparison for different sample sizes of loans in each node or product. This is evident in the calculations in the previously presented tables which always take into account the number of loans. An actual calculation that has been carried out to evolve the vintage comparison graph of Fig. 4 in accordance with Tables I, II and III is presented in Fig. 4A.

As described above, the Crus Classes method 34 delivers a comparison of two loan vintages either in the form of a graph or tabulated data which permits one to get a sense of which vintages are performing better. This information can then be used in making manual or automatic, computer generated yes/no decisions whether to originate, purchase, or to maintain and sell various vintages of loan products or servicing rights as needed at the decisional blocks 13, 24 and 32 of Fig. 1.

The basic premise of the Crus Classes analysis is that the future performance of these loan vintages will match the past pattern. This may not necessarily be true. To this end, the early warning system (EWS) 32 of the present invention further enhances the loan analysis process by incorporating an application of behavioral scoring that has been specifically designed to be used on closed end loans with longer maturities such as mortgages. The EWS 32 is able to statistically predict the probability that a group of loans will experience credit performance problems during a future preselected time period, without waiting for that loan to season. In the case of mortgages, the time to season is typically three to seven years. The EWS 34 is intended to provide management with automated analytical tools which allow

making decisions well in advance of the aforementioned three to seven "seasoning" period.

By utilizing the EWS, a mortgage originator can perform portfolio analysis and ascertain which product type, program, type of underwriting, property type, type of customer, origination channel, etc. is at risk, without waiting for the mortgages to actually mature and enter default. The only constraint is the amount of data attributes that the mortgage loan originator keeps on any customer over time, which for the purposes of the present invention may be two years. The mortgage originator can then dynamically adjust the flow of origination by altering any credit criteria derived from a particular attribute.

The EWS 34 constitutes the dynamic component of the underwriting concept of the present invention. With this concept, the decision maker can estimate improvements in credit quality for each specific type or amount of change in a criteria, i.e. he or she can calculate the marginal contribution of any attribute on record.

More specifically, the forward looking feature of the EWS component of the invention attempts to forecast the likelihood the borrowers will enter a 90+ days past due delinquency on their mortgages. This

condition -- the occurrence of a 90-day past due delinquency -- is defined as a "bad" condition relative to any loan. The EWS calculates the probabilities of bad conditions occurring by combining loan information with the credit bureau's current behavioral score for the given borrower. In other words, the EWS combines the borrower's current mortgage status (default status and age) with a forecast that is based on the borrower's performance on other obligations and uses this information to forecast the bad condition. The EWS system makes three major assumptions:

- The future performance pattern of defaults will be the same as in the past;
- The future performance depends upon the current loan characteristics and is dependent on past performance only through the credit bureau scores. Therefore, the EWS also carries all the assumption of the credit bureau's score that was used; and
- The EWS employs a logistic regression model to accurately and sufficiently predict default behavior.

The aforementioned "bad" condition is a discrete (yes or no) event that occurs when and if an individual loan is at least once three payments past due

at any point during a forward looking preset time period, for example, two years. Bad loans are assigned the value "1" and good loans the value "0". How many times the loan enters "bad" is not considered in the EWS. A good loan is never three payments past due over the aforementioned two year time frame and therefore is assigned a loan of a value "0". Preferably, in order to provide reliable information using the EWS system, the underlying portfolio should have at least 100,000 loans and the loans should consist of different distributions of ages, types, locations, etc. In an embodiment of the invention which has been reduced to practice the number of loans in the portfolio exceeded one million.

The EWS probability of loans entering the bad condition is developed or calculated on the basis of looking backward in time through a development period which may similarly constitute a two-year time period. The EWS formula considers the age of the loan at the beginning of development period; the credit bureau score for the loan at the beginning of the development period; the delinquency status at the beginning of the development period; and the type of product, for example, whether a government or conventional or adjustable rate mortgage, etc.

The following logistic model has been applied to the underlying portfolio (government and conventional loans being considered separately). In the formula shown below, P is the probability of a loan becoming bad at any time in the coming two years:

$$\mathrm{Log}(P/(1-P)) = A + (B_1 * AGE) + B_2 * C0 + B3 * D_1 + B4 * D_2 + B_5 * SCORE + B_6 * NO\ SCORE)$$

In the equation, AGE is defined in categories of quarters from 1-40. Therefore B_1 and AGE are 40 dimension row and column vectors respectively. SCORE is the mortgage score from a credit bureau rating company such as the well known Equifax rating bureau, at the beginning of the two-year time period, i.e. August 1994. Note, if no such score is available, the invention assigns the lowest possible value, namely 200. The Equifax scoring scores vary from 200 to 1000. The dummy variables in the above equation are defined as follows:

$$C0 = \begin{cases} 1 & \text{if the loan is current at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

$$D1 = \begin{cases} 1 & \text{if the loan is 1 month past due at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

$$D2 = \begin{cases} 1 & \text{if the loan is 2 months past due at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

$$\begin{matrix}NO\\SCORE\end{matrix} = \begin{cases} 1 & \text{if the loan has no credit score available at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

The coefficients A, B_1, B_2, B_3, B_4, B_5 and B_6 are estimated by running the model over the underlying portfolio.

All of the forecasting is done at the individual loan level and then the results are aggregated into the portfolio of interest by defining or grouping certain loan characteristics (location, rate type, maturity, LTV, etc.) to make comparisons. Even though the invention presents the mean probability for a predicted group, the information contained in the individual loan level data is preserved because the invention explicitly considers the dispersion around the mean of the bad rate over time.

To forecast the probability of an individual loan entering 90+ day default during the predetermined time period (i.e. the two year time frame), all one need do is insert the estimated coefficients and the characteristics of that individual loan into the logistic equation for "P" presented earlier.

The logistic model in the form of the aforementioned equation provides numerical results which are suitable of being graphically presented as shown in Fig. 5. The graph enables management to readily interpret and form decisions based on the predictions which it contains. In accordance with a further embodiment of the invention, the results are feedback by

the computer which then provides yes/no decisions based on predetermined default risk or profit criteria set by the operator.

Fig. 5 is a snapshot taken in 1996 and depicts loan experience looking both backwards to the past two years and forwards over a similar two year time span. The vertical solid bars 72 represent the current mean (expost) bad rates for a particular group over the past two years. In other words, these bars show the mean bad rate percentages of a group of loans that originated in a particular year. For example, the bar 72 for the loans originated in 1989 shows a bad rate of about 12.5%. The score for the 1991 loans is just about 8% whereas the bad rate for 1996 is quite low (under 5%), reflecting the fact that this vintage of loan has not yet matured sufficiently.

The hatched vertical bars 74 represent the forecasted mean bad rates (exante) for the same group of loans over the next two years. The value for the 1996 vintage is somewhere around 7% indicating an expected delinquency rate of 7% even though the past two-year performance had an actual bad rate of only about 2.5%. The curve 76 represents the expected bad rate curve that is obtained by modifying the forecasted bad rates by the

risk ratio on nearby vintages, and this shall be explained more fully later on.

One should not place much emphasis on whether the curve 76 is above the solid bars 72, since this may merely reflect the normal pattern of seasoning for mortgages. Nor should one place much emphasis on the absolute height of each bar, since this may reflect different expectations among the various groups or types of loans that are being analyzed. Instead, the graph of Fig. 5 indicates three important benchmarks for reviewing and forecasting the risk in the given loan portfolio. First, note the jump which is indicated by the arrow 84. It represents a jump which occurs when the difference between the hatched bars 74 and the solid bars 72 is greater than one standard deviation above the historical age weighed performance for that vintage. The bigger the jump, the more serious the quality problem. This measure is particularly useful on younger vintages, e.g. the 1996 vintage to which the arrow 84 is pointed.

Second, the size of the portion of the hatched bars 74 which protrudes above the expected bad curve 76 indicates an unusual level of risk in the past or the future for that group of loans. Note the arrows 80 and 82 which indicates such conditions. Finally, the arrow 78 indicates a turning point which represents the point

at which the first derivative of the expected BAD rate curve changes sign from positive to negative: i.e. the first time the bad rate drops as the loans age increases. The younger the age at which the turning point occurs, the earlier the portfolio's credit performance will or has matured.

The manner in which the curve 76 of Fig. 5 is derived may be better understood by reviewing Figs. 6 and 7. More specifically, the curve 86 is developed by taking a snapshot at a point in time looking at loans of different quarterly ages and asking how many in each age group entered the "bad" state during the preceding predetermined time period, e.g. two years.

Initially, the EWS 34 develops for each empirical two-year period of performance the bad rate curve as a function of age in quarters. See the quarterly bad rate curve 86 in Fig. 6.

Next, using a moving average, the invention smooths each curve to reduce the randomness of the quarterly performance, thus obtaining the smooth curve 88 in Fig. 6. In fact, the slopes of the yearly bad rate curve are calculated as the percentage change in bad rates from one year to another year, which is known as the risk ratio. To improve the integrity of the results and protect against possible statistical aberrations, at

least eight two-year time periods are considered, with the means and standard deviations of the risk ratios calculated.

To find the point on line 76 for 1991, the invention uses the point on line 76 for 1990 which has the expected bad rate for 1990. Multiplying this bad rate by the corresponding mean risk ratio from Fig. 6 obtains the expected bad rate for 1991 and its standard deviation. This expected bad rate is used for the point on line 76 for 1991. However, if the forecast bad rate (bar 74) is within the expected bad rate, plus or minus one standard deviation, the invention just substitutes the expected bad rate by the forecast bad rate so that the line 76 passes through the top of bar 74.

The third in the triad of dynamic underwriting tools of the present inventions, the matrix link system 36, uses the information developed by the Crus Classes technique 34 and early warning system 32 to develop a probability based prediction of how many of a given set of loans will be "bad" at a selected future date.

More specifically, while the Crus Classes method 34 analyzes the past performance of loan vintages and the EWS system places a probability on a group of loans entering the bad state within a preset time frame, i.e. a window, the matrix link system 36 is designed to

predict the default status performance of a group of loans at a preset point in time within the window of operation of the EWS. For example, the EWS method is able to say with respect to a group of loans that 3% of those loans will enter a bad state (90+ days in arrears) at one time or another during a two year window. In comparison, the matrix link is designed to answer the question how many loans will be non-accruing, i.e. in the 90+ payment overdue state, at the end of the first quarter of the two year window or nine months into the window and so forth, taking into consideration that some loans may enter the bad state or exit therefrom due to prepayment or on account of having been matured, or by completing foreclosure.

To perform its functions, the matrix link system 36 predicts how many borrowers that enter a 90-days delinquency state remain there, how many loans will return to "good" status and, finally, in which quarter over the predefined window, e.g. two years, will these transitions occur. Note that a particular loan can enter a bad state, return to a good state or remain in a bad state. Loans may mature, pay off or complete foreclosure during the predefined window period and thus exit the loan portfolio being analyzed. In order to provide a quantitative measure of the transitions of

loans between different states, the present inventors have developed a so-called delinquency transition matrix in a form which, in one embodiment thereof, appears as in the table in Fig. 7.

In the table of Fig. 7, use is made of a historical file spanning four years and including vintage years 1993-1996. The table shows the delinquency performance of a particular group of loans. Further, the table stratifies the loans by age of origination. Note that the table lists separately the results for three different types of loans, namely conforming loans, jumbo loans and government loans. In each case, it shows the probability of a loan transitioning (a) from a bad state to a bad state, (b) from a bad state to a good state; (c) exiting, i.e. maturing and therefore being dropped from the sample of loans being considered, (d) from good to bad, (e) from good to good; and (f) from good to exit state.

Using the percentages listed in the delinquency transition matrix in the Table of Fig. 7, one can then begin to convert the information obtained through the EWS system 32 into the forecasts of how the Crus Classes vintages will perform at predefined time periods within the window. The table in Fig. 8 illustrates the formulae evolved by the present inventors which are as follows.

First, the current age of the loan at the time of forecast is determined. In the table of Fig. 7, the age of the loans is indicated in years (1, 2, 3, 4... 10). However, in an actual implementation of the invention, the vintages have been stated and the formula is calculated in terms of quarters to obtain increased accuracy.

For each group of loans of a particular age, the invention uses a 3-month transition matrix to forecast three months forward, a 6-month transition matrix to forecast six months forward, a 9-month transition matrix to forecast nine months forward and a 12-month transition matrix to forecast twelve months forward.

Based on the choice of data in the previous step, the invention calculates respectively looking forward three, six, nine and twelve months:

1. how many good loans and bad loans will exist from the portfolio;

2. how many good loans will turn into bad; and

3. how many bad loans will remain bad.

From the above data, one obtains the classic "roll-rate" forecast which provides the first component of the forecast. The above approach merely projects

forward the results that have already occurred in the past, on the expectation that they will repeat themselves. However, a greater benefit of the matrix link technique of the present invention comes from adding the additional information that is contained in and/or obtained by the early warning system 32.

To this end, the invention:

(a) Calculates an empirical ratio obtained as -- the cumulative number of loans which are 90+ at each quarter (EOP) and divides it by the number of loans that are 90+ at least once during these four quarters.

(b) From the EWS, the invention obtains or forecasts the "bad" rate for the two-year window based on the EWS method 32.

(c) Using the EWS, the invention forecasts the bad rate and the empirical ratio above as a new piece of information to adjust the classic "roll-rate" forecast. This is in essence what comprises the "matrix link" method 36. Fig. 9 provides the results of the matrix link in graphical form. In the example shown, the performance of different vintage loans is predicted one year forward in quarterly installments starting in 1997.

For example, the plot 102 shows the two-year performance of 1995 vintage loans which range in age (months) from 0 to 24 months, as viewed looking backwards in time in 1997. The curve 104 shows the delinquency rate percentages predicted for the next twelve months. For example, when the groups of loans attain an age of 27, the delinquency rate can be read on the ordinate axis. The same is true for this group of loans when they reach an age of 30 months, 33 months and 36 months. The reason that the curve 104 has a predicted value below the actual value is that the prediction in the matrix link uses a moving sum average which weighs down the actual sharp up-turn in the "bad" rate which has actually occurred toward the end of the curve 102.

The above remarks are also applicable to the curves 106, 108 which apply to the 1993 vintage, the curves 110 and 112 which are applicable to 1994 vintage, and to the curves 114 and 116 which apply to the 1996 vintage.

Note that the Crus Classes are less static than traditional mortgage vintage analysis. Therefore, the performance of the last three points of any vintage can still change somewhat, for better or worse.

The matrix link lines, i.e. the curve 104, 108, 112, and 116 also show where the inventors expect the

last three Crus Classes points to adjust over the next nine months.

The system of the present invention lends itself easily to being implemented through use of a general purpose programmable computer as illustrated in Fig. 10. Thus, the general purpose computer 124 communicates with a local database 122 which receives a wealth of statistical and specific information about various loans from diverse sources. For example, the source of the information may be a national loan database 120 which is maintained by certain industry groups. The general purpose computer 124 has the usual complement of peripherals including an operator's console 126, ROM 128, RAM 130 and a hard disk 132.

The computer 124 operates under control of major software blocks which perform the dynamic analysis 134 in a manner already described. The main software components are the software routines 136 which handle the development and analysis of the Crus Classes associated with the creation of the loan vintages. The early warning system block 138 calculates probabilities of loans going bad within a predetermined forward looking window. Finally, the matrix link software block 140 forecasts the probabilities that a fraction of loans will go bad within the window at a particular time.

The analytical results developed by these software subroutines or blocks 136, 138 and 140 are tabulated in the tabulation software block 150 and outputted through an output software block 152. The output can be in the form of a signal which drives a printer which generates a graphical representation of the results in the manner previously described. Alternatively, the output may supply the results to the console 126 for visual inspection by the operator. Alternatively, the operator may program the computer 124 via the console 126 to provide yes/no answers as to whether an investment should be made or continued to be made in a particular loan portfolio, again as already described.

Although the present invention has been described in relation to particular embodiments thereof, many other variations and modifications and other uses will become apparent to those skilled in the art. It is preferred, therefore, that the present invention be limited not by the specific disclosure herein, but only by the appended claims.

WHAT IS CLAIMED IS:

1. A process for analyzing and selecting loan portfolios, wherein each loan portfolio comprises a plurality of loan units, the process including the steps of:

separating the loan portfolios into a plurality of loan vintages in a manner such that the loans included in each loan vintage have origination dates that are on average of the same age and said origination dates of each loan portfolio are all within a first time interval and the respective time periods of the different loan vintages being mutually exclusive of one another;

counting a bad rate of the loans in each loan vintage by counting the loans in each loan vintage on which payments are in arrears for a time period greater than a second time interval during a time window having a third time interval, wherein the third time interval is substantially greater than said second time interval; and

providing a comparison of the bad rates of the different loan vintages on a visually perceivable output medium, to allow comparing the bad rates of the different loan vintages.